



# Policy impact of national comprehensive pilot initiative for new-type urbanization on carbon emissions from rural energy consumption in China

Man Wang<sup>1</sup> · Manman Gao<sup>1</sup> · Huimin Cao<sup>1</sup> · Zhenyu Yan<sup>1</sup> · Muhammad Taimoor<sup>1</sup> · Jiapeng Xu<sup>1</sup>

Received: 13 January 2024 / Accepted: 29 June 2024  
© The Author(s), under exclusive licence to Springer Nature B.V. 2024

## Abstract

With the coordinated advancement of China's new-type urbanization (NTU) and the "dual carbon" objectives, the government is increasingly prioritizing green and low-carbon development in rural areas. Based on the provincial panel data from the China Energy Statistical Yearbook spanning the years 2010 to 2019, this study employs a rigorous Difference-in-Differences (DID) model to conduct an in-depth analysis of the impact of NTU on carbon emissions from rural energy consumption (CEREC) and its underlying mechanisms. Furthermore, we explore the decoupling dynamics between urbanization development levels and CEREC across various stages and provinces. Our findings highlight the catalytic effect of the National Comprehensive Pilot Initiative for New-Type Urbanization (NCPINTU) initiatives on CEREC. Compared to non-pilot provinces, rural per capita carbon emissions have increased by an average of 1.278 tons per year, and the spillover effect from neighboring provinces is significant, resulting in an average increase of 1.219 tons per year. Mechanism analysis indicates that NTU affects rural energy consumption intensity (ECI) and energy consumption structure (ECS) across multiple dimensions, including population, economy, society, ecology, and space, thereby influencing CEREC. Furthermore, our expanded analysis reveals spatial and temporal disparities in the decoupling status of provinces, with western regions generally exhibiting poorer decoupling statuses. These findings deepen our understanding of the performance and mechanisms of achieving the "dual-carbon" objectives through NTU, also underscore the imperative to foster a new era of low-carbon and environmentally sustainable rural development.

**Keywords** NCPINTU · DID · CEREC · ECI · ECS

## Abbreviations

NTU	New-type urbanization
NCPINTU	The national comprehensive pilot initiative for new-type urbanization
CEREC	Carbon emissions from rural energy consumption
ECI	Energy consumption intensity
ECS	Energy consumption structure
DID	Difference-in-differences

Extended author information available on the last page of the article

## 1 Introduction

Since initiating reforms and the opening up policy, China has undergone the world's fastest and largest urbanization process, achieving internationally recognized milestones. At present, establishing a new development pattern, with a primary focus on domestic circulation and supplemented by synergies between domestic and international circulations, represents a significant decision by the Chinese government in response to the current developmental stage and changes in both domestic and global environments. As a crucial driver for advancing economic circulation and shaping a new development paradigm, NTU effectively leverages China's vast market scale and taps into latent demand within urban–rural areas. In 2014, the State Council issued "the National New-type Urbanization Plan (2014–2020)", designating Jiangsu Province, Anhui Province, and 62 other cities (towns), including Ningbo, as pilot areas. Aligned with each pilot initiative's objectives and overarching goals, the emphasis is placed on fostering integrated urban–rural development and facilitating the establishment of new rural areas. By 2023, China's per capita urban consumption expenditure has increased by 84.91%, and rural per capita consumption expenditure has increased by 116.81%. It can be seen that NTU has significant advantages in further improving the consumption level of rural residents. With the rapid increase in rural residents' consumption levels, the demand for energy-intensive products also grows. Consequently, the energy consumption required to sustain household operations will increase synchronously, potentially leading to an increase in CEREC.

Since the onset of the twenty-first century, China has consistently held the position of the world's largest emitter of carbon dioxide (Lu & Chen, 2023). At the 26th United Nations Climate Change Conference (COP26), nearly 200 countries reached a joint communiqué known as the "Glasgow Climate Agreement," with the shared objective of limiting global warming to within 1.5 degrees Celsius. In response to the pressing issue of global climate change, China has pledged to intensify its efforts to reduce carbon emissions (Cheng et al., 2023). The "Opinions on Fully, Accurately, and Comprehensively Implementing the New Development Philosophy and Advancing Carbon Peak and Neutrality Efforts" issued by the State Council in 2021, integrates "carbon peaking and carbon neutrality" into overall economic and social development strategies, with a particular focus on energy conservation and emission reduction in key energy-consuming industries. Scholarly research on carbon emissions has primarily focused on urban industrial sectors (Shao et al., 2019; Wang et al., 2020; Yan et al., 2016). In fact, emissions from daily life have become the primary source of carbon emissions in some developed countries (Li & Zhang, 2016). While the consumption levels in urban and rural areas are continually rising during the advancement of China's NTU, the disparities between them are also narrowing. With daily life carbon emissions gradually becoming the second largest source of carbon emissions in China, the contribution of rural household energy consumption to carbon emissions is increasing year by year, once exceeding that of urban areas (Shen et al., 2017). Although rural areas in China are gradually transitioning from traditional biomass burning such as straw and firewood to renewable energy sources such as solar energy, biogas, and electricity, the proportion of the latter in rural household energy consumption remains low (Clausen & Rudolph, 2020). The practical issue of CEREC remains severe, requiring more profound research and targeted solutions. In the process of pilot work and the transformation of China's rural energy consumption patterns, how much impact will NTU have on carbon emissions from rural household energy consumption? What are the underlying mechanisms? How can targeted measures be formulated to implement a low-carbon

development path in the construction of NTU? Objectively answering the above questions can provide critical essential insights for promoting NTU and achieving carbon emission reduction commitments in China, as well as for formulating policies for low-carbon development of rural energy.

In response, academia has engaged in extensive discussions on China's daily carbon emissions issue, with existing literature primarily focusing on the following aspects: Firstly, regarding the measurement of daily carbon emissions, most studies focused mainly on urban areas or the overall measurement of urban and rural lifestyle carbon emissions. The primary measurement methods include three types. The first method is the emission coefficient method, which calculates direct carbon emissions by multiplying the energy carbon emission coefficient by the corresponding energy consumption (Ji et al., 2016; Wang et al., 2019; Yu et al., 2019). The second method is the input–output method (Liu et al., 2023; Yu et al., 2022), which measures the energy use and greenhouse gases embedded in consumer goods and services at the macro level. Additionally, some scholars adopt the lifestyle method (Zhang et al., 2023), primarily calculating the energy intensity of each consumption activity based on household consumption expenditure data associated with lifestyles (Meng et al., 2023). There has been sufficient research on the measurement of carbon emissions at the urban level, while there is a relative lack of research on the measurement of CEREC. Secondly, the study of factors affecting daily carbon emissions is another critical area of research. At the micro-level, factors such as socioeconomic status, population size, geographic location, income and expenditure levels, consumption behaviors, household and housing attributes, and household characteristics significantly influence energy demand (Bhattacharyya, 2015; Du et al., 2021a, 2021b), thereby impacting household carbon emissions (Zhang et al., 2019). At the macro-level, scholars have explored the relationships between economic growth, energy efficiency, housing area, and carbon emissions (Cheng & Da, 2022; Deng & Zhong, 2023; Gao & Han, 2022). Thirdly, the relationship between urbanization and carbon emissions is also a focus of research, with existing studies predominantly focusing on urban carbon emissions. This relationship can be categorized into three primary perspectives: Firstly, urbanization and carbon emissions exhibits a linear relationship. As one of the driving factors for carbon emissions, an increase in the urbanization rate promotes the growth of urban carbon emissions (Wang et al., 2016). For every 1% increase in the urbanization rate, energy consumption carbon emissions increase by 0.151% (Huang et al., 2016). However, improvements in the quality of urbanization can reduce carbon emissions (Tao et al., 2016). Additionally, urbanization and carbon emissions display a nonlinear relationship (Wang et al., 2021). From a longitudinal perspective, in the early stages of urbanization, carbon emissions increase with economic growth, but once urbanization reaches a certain level, economic growth can inversely suppress carbon emissions (Chen et al., 2019). The relationship between the level of urbanization and carbon emissions exhibits a "positive U-shaped" curve, initially decreasing and then increasing (Yang et al., 2023). Exploring the horizontal dimension, urbanization promotes household carbon emissions in various provinces, but with significant regional disparities (Yang et al., 2022; Zheng et al., 2018). Lastly, some studies argue that there is no significant relationship between urbanization and carbon emissions.

In summary, existing research primarily concentrates on measuring household carbon emissions, examining factors that influence household carbon emissions (Y. Liu et al., 2022a, 2022b), and assessing the impact of urbanization on carbon emissions. Nevertheless, the research focuses predominantly on urban households (Li & Gao, 2022), with CEREC receiving inadequate attention. Additionally, regarding studies on the factors influencing carbon emissions, while most scholars have explored the aspect of urbanization,

there is a noticeable gap in research concerning the pathways and mechanisms of influence. Against the backdrop of vigorously promoting the construction of NTU, studying the relationship between urbanization and CEREC, along with their mechanisms of action, and proposing targeted measures, is of great significance for achieving coordinated development between NTU and the reduction of CEREC. Potential innovations of this study: First, this study focuses on CEREC, and utilizes the institutional reform of NCPINTU in 2014 as a quasi-natural experiment. It quantitatively evaluates its impact on CEREC using DID, effectively addressing gaps in previous research. Second, the study investigates the impact mechanism of NTU on two intermediary variables: ECI and ECS, starting from five dimensions—population, economy, society, ecology, and space. This approach provides robust empirical evidence that contributes to understanding the relationship between NTU and CEREC.

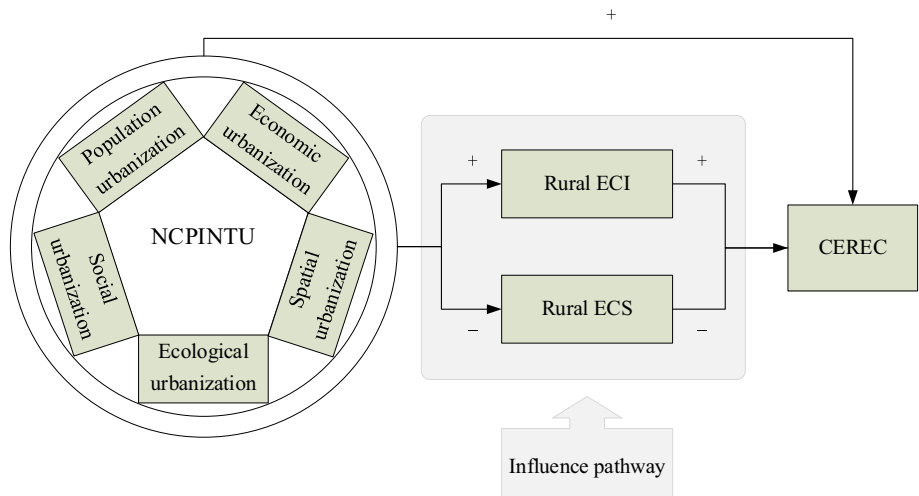
The remainder of this study is organized as follows: Sect. 2 develops hypotheses and analyses the mechanisms. Section 3 introduces data and variable definitions. Section 4 explains the main research methods. Section 5 presents the results and discussions, and Sect. 6 details the conclusions and implications.

## 2 Research hypotheses and impact mechanisms

Diverging from traditional urbanization centered on urbanization rate, NTU is a multidimensional urbanization focusing on dimensions including population, economy, society, ecology, and space (Chen et al., 2018; Yang & Sun, 2015; Yu, 2021) with its core principle being people-oriented (Chen et al., 2019; Deng & Zhong, 2023; Fang, 2019). Compared to the extensive urbanization model, NTU emphasizes integrating urban and rural development (Liu et al., 2016). Embracing the path of NTU requires a heightened emphasis on the equalization of essential urban–rural public services, ensuring that all residents share the benefits of modernization. However, there is still a considerable gap in urban–rural development in China at present, necessitating accelerated rural development to narrow the urban–rural disparity, which serves as a crucial breakthrough for the leap-forward development of NTU.

With the migration of agricultural populations to urban areas during urbanization, rural population density decreases, leading to significant shifts in age distribution and subsequently altering rural residents' lifestyles and consumption patterns. As rural population density declines, there is an increase in per capita residential area and infrastructure, resulting in higher per capita resource ownership among rural residents. This, in turn, leads to a rise in energy consumption required to sustain these resources (Cao et al., 2021). Additionally, as rural living standards improve, household energy consumption gradually increases, promoting CEREC.

ECI refers to the ratio of energy consumption to actual household consumption, with energy consumption uniformly converted into standard coal consumption for this study. With the implementation of NTU, a considerable number of rural laborers migrate to urban areas, leading to a heightened input of agricultural machinery in the agricultural production process. The advancement in agricultural mechanization levels implies a greater demand for fossil fuels such as diesel and gasoline. Consequently, NCPINTU contributes to an increase in ECI, indicating that household energy consumption expenditure rises as a proportion of household income. As a result, CEREC increases correspondingly at the same consumption level.



**Fig. 1** Impact mechanism of NCPINTU on CEREC

ECS refers to the ratio of household electricity consumption to standard coal energy consumption (Han & Wu, 2018; Liu et al., 2022a, 2022b). Urbanization has propelled improvements in rural living standards, thereby increasing household demand for energy, particularly electricity (Qiu et al., 2015). However, the energy supply in rural areas may not meet the rapidly growing demand during the urbanization process, leading to a reliance on traditional high-carbon energy sources such as coal and fuel. Furthermore, inadequate infrastructure development in rural areas, including electricity supply and clean energy facilities, constrains the use of clean energy and exacerbates the reliance on high-carbon energy sources. Additionally, imbalances in resource utilization in rural areas may result in a skewed distribution of clean energy supply, hindering the optimization of ECS.

Based on the above discussions, this study proposes the following hypotheses:

**Hypothesis 1.** NCPINTU promotes CEREC in China.

**Hypothesis 2.** NCPINTU promotes the increase in rural ECI, thereby leading to an increase in CEREC in China.

**Hypothesis 3.** NCPINTU inhibits the optimization of rural ECS, thereby promoting CEREC in China.

NTU emphasizes coordinated development across population, economy, society, ecology, and space, analyzing its influence on ECI and ECS from various dimensions. The constructed influence mechanisms are illustrated in Fig. 1:

### 3 Data sources and variable definitions

#### 3.1 Data sources

The data for this study are sourced from several official publications, including "the National New-type Urbanization Plan (2014–2020)"<sup>1</sup> released by the State Council of China, the "2006 IPCC Guidelines for National Greenhouse Gas Inventories"<sup>2</sup> published by the Intergovernmental Panel on Climate Change, as well as the "China Statistical Yearbook" and the "China Energy Statistical Yearbook" covering the years 2010–2019, both published by the National Bureau of Statistics of China.<sup>3</sup> The data encompass information on the pilot provinces and implementation plans for NCPINTU, as well as the primary types and consumption levels of household energy in rural China, macroeconomic development indicators, and household economic conditions. Statistical analysis reveals that rural energy consumption in China comprises 26 energy types, including raw coal, washed coal, shaped coal, coke, coke oven gas, blast furnace gas, crude oil, gasoline, kerosene, diesel, fuel oil, lubricating oil, liquefied petroleum gas, refinery dry gas, natural gas, liquefied natural gas, heat, electricity, biogas, straw, firewood, among others. These data are sourced from regional energy balance sheets published in China's energy statistical yearbooks. For consistency and methodological completeness, data from Hong Kong, Macau, Taiwan, and the Tibet Autonomous Region are excluded from the analysis.

NCPINTU encompasses various administrative levels, including provinces, municipalities, counties, and towns. It comprises two provinces, Jiangsu and Anhui (as indicated by the black triangles in Fig. 2), as well as 10 cities, consisting of three prefecture-level cities and seven provincial capitals, in addition to several prefecture-level cities (districts, counties), and towns. Considering data availability, this study designates the provincial pilot areas as the experimental group and other provinces as the control group for research purposes.

#### 3.2 Variable definitions and descriptive statistics

(1) Dependent variable: The dependent variable in the model is CEREC, encompassing carbon emissions from the complete combustion of 26 major energy sources, including raw coal, cleaned coal, coke, and others. The calculation formula for CEREC is as follows:

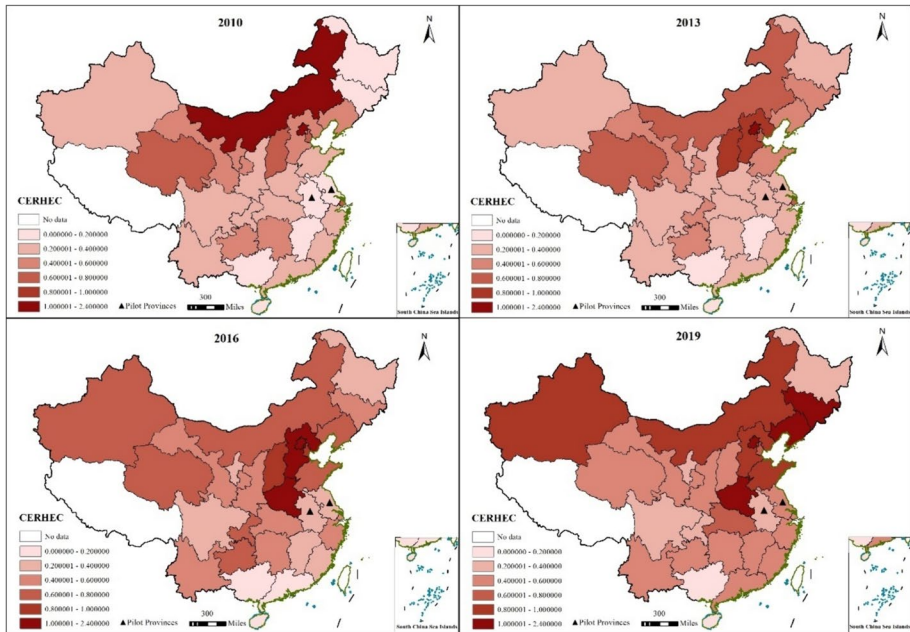
$$p = \frac{44}{12} \times \sum_i^n \alpha_i F_i \beta \quad (1)$$

where  $p$  represents CEREC (Huang et al., 2022).  $F_i$  denotes the consumption quantity of each energy source,  $\alpha_i$  represents the coal conversion coefficient for the  $i$ -th energy source, indicating the amount of standard coal that can be converted from one unit of the energy source.  $\beta$  is the carbon emission coefficient for energy sources, which is 0.7326 tons of carbon emitted per ton of standard coal completely consumed. The atomic weight of carbon is

<sup>1</sup> <https://www.gov.cn/xinwen/site1/20150204/40201423027629790.pdf>

<sup>2</sup> <https://www.ipcc.ch/>

<sup>3</sup> <https://www.stats.gov.cn/sj/ndsj/>



**Fig. 2** Distribution of carbon emissions from rural life in China. *Note:* This figure is based on the standard map with the approval number GS (2023)2767 downloaded from the National Administration of Surveying, Mapping, and Geoinformation’s Standard Map Service website. The basemap has not been modified

12, and the molecular weight of  $CO_2$  is 44. As shown in Fig. 2, draw distribution maps of CEREC for 2010, 2013, 2016, and 2019.

(2) Core explanatory variable: The core explanatory variable is NCPINTU. Variable definitions and descriptive analysis are shown in Table 1. Initiated under the framework of "the National New Urbanization Plan (2014–2020)," provinces and cities initiated the application process for NCPINTU. Starting in 2014, Jiangsu and Anhui provinces became the pilot provinces. The program’s key focus is people-oriented development, implementing the spirit of central meetings, emphasizing the improvement of urbanization quality, and taking people as the starting point and foundation of urbanization. NCPINTU serves as a platform for exploring and disseminating replicable experiences for the nationwide promotion of NTU. This study adheres to the national guidelines for NCPINTU and constructs the variable representing the pilot program’s reforms using the DID methodology. Utilizing data from 30 provinces across the country, the pilot program provinces are categorized as the treatment group, with the remaining provinces designated as the control group. As depicted in Fig. 2, the provinces marked with black triangles represent the experimental group.

(3) Mediating variables: As rural residents’ consumption levels improve and lifestyles undergo transformation, their reliance on energy gradually increases, and the proportion of various energy sources consumed in the process changes accordingly. Therefore, the mediating variables examined in this study are ECI and ECS, which elucidate the mechanism through which NCPINTU influences CEREC. ECI represents the proportion of energy consumption relative to total household consumption, while ECS

**Table 1** Variable definition and descriptive statistics

Variable type	Variable name	Variable symbol	Definition	Mean	Standard deviation
Dependent Variable	CEREC	<i>Per_C</i>	The ratio of rural household CO <sub>2</sub> emissions to rural population	0.531	0.353
Core explanatory variable	NCPINTU	<i>Treat*period</i>	Treatment group provinces have a value of 1 for the execution year and onwards, otherwise 0	0.040	0.196
Mediating variables	ECS	<i>Con</i>	Proportion of electricity consumption in total household energy consumption	0.265	0.206
	ECI	<i>Int</i>	Ratio of rural energy consumption of standard coal to actual consumption expenditure (ton/10,000 yuan)	0.227	0.142
Control variables	Per capita consumption level	<i>Csm</i>	Ratio of total rural household consumption to rural population (10,000 yuan)	1.079	0.585
	Per capita disposable income of rural households	<i>Per_income</i>	Ratio of total rural household income to rural population	1.154	0.514
	Level of mechanization	<i>Mac</i>	Total power of agricultural machinery (10 million kilowatts)	3.369	2.924
	Rural population size	<i>Pop</i>	Rural population (in millions)	19.989	13.145
	Industrial structure	<i>I</i>	$I = 1 \times I_1 + 2 \times I_2 + 3 \times I_3$	2.381	0.125
Explanatory variables	Level of urbanization	<i>Urb</i>	Urbanization rate of each province	0.571	0.124



denotes the cleanliness of energy consumption. The advancement of NCPINTU brings about transformations in rural residents' production and living styles. The enhancement in consumption levels and quality of life leads to shifts in energy demand, thereby impacting household ECI and ECS, and ultimately influencing CEREC.

(4) Control variables: Drawing on previous research, the control variables in this study include rural per capita disposable income, rural per capita consumption level, rural population size, level of mechanization, and coefficient of industrial structure upgrading (Sun & Sun, 2016). Rural per capita disposable income is represented by the ratio of total rural household income to the rural population; rural per capita consumption level represents the ratio of total rural household consumption to the rural population, measured using the actual per capita consumption expenditure of rural residents in 2003 at constant prices; rural population size is represented by the rural population in the respective year; the level of mechanization indicates the extent of agricultural mechanization in rural areas, measured by the quantity of large-scale machinery per thousand people; additionally, industrial structure assesses the comprehensive development status of the primary, secondary, and tertiary industries, measured by the coefficient of industrial structure upgrading. With the increase in rural per capita disposable income, consumption levels further rise, and higher consumption levels are typically associated with increased energy use, such as purchasing more appliances, vehicles, etc., thereby leading to CEREC (Qu et al., 2014); hence rural per capita consumption level and rural per capita disposable income are selected as control variables. In agricultural production and management, machinery substitutes for household labor, and with the acceleration of urbanization, rural population size is declining, further promoting the level of mechanization, significantly improving the efficiency of energy utilization (Liu et al., 2021), thereby affecting household energy allocation and subsequently influencing CEREC, hence rural population size and level of mechanization are selected as control variables. Studies have shown that different industrial structures have different impacts on carbon emissions (Zhao et al., 2023), with an agricultural-dominated industrial structure potentially leading to more biomass energy use, such as wood and straw burning, which increases household carbon emissions. In contrast, a more diversified and modern industrial structure may drive rural areas towards cleaner and renewable energy sources, thus reducing carbon emissions. Therefore, changes in industrial structure may directly affect CEREC. Hence industrial structure is selected as a control variable.

(5) Mechanism variables: China has embarked on a new trajectory of high-quality urbanization development. In the face of intricate domestic and international circumstances, market scale fluctuations, and increased demand uncertainties, the central government has proposed the "dual-circulation development pattern with domestic circulation as the mainstay and domestic-international circulation reinforcing each other." In response to this, actively promoting high-quality urbanization as well as expanding domestic demand is the current imperative. Diverging from the conventional urbanization model primarily focused on the urbanization rate, NTU prioritizes the integrated and synchronized development of population, economy, society, and ecological environment. Its basic principles include people-oriented urbanization, promoting the coordinated development of industrialization, informatization, urbanization, and agricultural modernization, optimizing spatial structure and layout, and paying more attention to the overall coordinated development of urban and rural areas (Li et al., 2020).

In this study, we construct NTU development indicators from five dimensions (Lin & Zhu, 2021): population, economy, society, ecology, and space. The scores of each dimension are calculated using the entropy method, as shown in Table 2.

**Table 2** Index system of NTU

Objective layer	Criterion layer	Symbol	Indicator layer	Attribute
Level of new urbanization development	Population urbanization 0.045 (0.014)	<i>UPop</i>	Urbanization rate of permanent population (%)	+
			Urban population density (people/km <sup>2</sup> )	+
	Economic urbanization 0.070 (0.022)	<i>UEco</i>	Registered urban unemployment rate (%)	-
			Urban-rural per capita income ratio (%)	-
	Social urbanization 0.095 (0.043)	<i>USoc</i>	Share of secondary industry value added in GDP (%)	+
			Share of tertiary industry value added in GDP (%)	+
			Fixed asset investment growth rate (%)	+
			Per capita GDP (yuan)	+
			Per capita local fiscal revenue (100 million yuan)	+
			Per capita retail sales of social consumer goods (yuan)	+
	Ecological urbanization 0.065 (0.026)	<i>UEnv</i>	Per capita urban resident expenditure (yuan)	+
			Per capita rural resident expenditure (yuan)	+
			Number of public transport vehicles per ten thousand people	+
			Number of university students per ten thousand people	+
Number of high school students in the secondary education stage per hundred thousand people			+	
Number of books in public libraries (ten thousand copies)			+	
Forest coverage rate (%)		Per capita park green space area (m <sup>2</sup> )	+	
		Forest coverage rate (%)	+	

**Table 2** (continued)

Objective layer	Criterion layer	Symbol	Indicator layer	Attribute
			Harmless treatment rate of domestic waste (%)	+
			Average daily sewage treatment capacity (ten thousand cubic meters/day)	+
			Number of hospitals and clinics (units)	+
Spatial urbanization		<i>USpa</i>		
0.072			Number of hospital beds per ten thousand people	+
(0.028)			Per capita urban road area (m <sup>2</sup> )	+
			The proportion of built-up area an in urban area (%)	+

## 4 Model specification

### 4.1 Baseline regression model

DID is constructed to examine the impact of NCPINTU on CEREC:

$$\ln Per\_C_{pt} = \alpha + \beta did_{pt} + \delta x_{pt} + \tau_t + v_p + \varepsilon_{pt} \quad (2)$$

where  $t$  represents the year,  $p$  represents the province, and  $Per\_C_{pt}$  represents the dependent variable, CEREC in the  $p$ -th province in year  $t$ .  $did_{pt}$  is the core explanatory variable of the baseline regression model used to identify NCPINTU.  $X_{pt}$  represents the control variables in this study, including rural economic development level, industrial structure, infrastructure construction, mechanization level, and per capita consumption level.  $\tau_t$  and  $v_p$  represent year fixed effects and province fixed effects, respectively, and  $\varepsilon_{pt}$  is the error term.

### 4.2 Mechanism analysis

#### 4.2.1 Fixed effects model

NTU is not only reflected in the urbanization of people but also manifests in various dimensions such as economy, society, ecology, and space. From different dimensions, we investigate how NTU affects rural ECI and ECS through different pathways. By conducting a Hausman test, we ultimately adopt a time fixed effects model:

$$y_{it} = \alpha_0 + x_{it}\beta + u_i + \varepsilon_{it} \quad (3)$$

where  $y_{it}$  represents the dependent variable of ECI and ECS,  $\alpha_0$  is the intercept term,  $\beta$  measures the degree of impact of indicators from different dimensions of NTU on ECI and ECS,  $x_{it}$  represents the five dimensions of the core explanatory variable, NTU Index,  $u_i$  represents time fixed effects, and  $\varepsilon_{it}$  represents the random error term. Subscripts  $i$  and  $t$  represent provinces and years, respectively.

#### 4.2.2 Mediation effect test

Based on the theoretical foundation analyzed earlier, we empirically analyze the impact pathway of NCPINTU on CEREC using the two mediation variables, ECI and ECS.

$$\ln per\_C_{pt} = \alpha + \beta did_{pt} + \delta x_{pt} + \tau_t + v_p + \varepsilon_{pt} \quad (4)$$

$$\ln M_{pt} = \alpha + \beta_2 did_{pt} + \delta x_{pt} + \tau_t + v_p + \varepsilon_{pt} \quad (5)$$

$$\ln per\_C_{pt} = \alpha + \beta_3 did_{pt} + \gamma \ln M_{pt} + \delta x_{pt} + \tau_t + v_p + \varepsilon_{pt} \quad (6)$$

In Eqs. (4) to (6),  $M_{pt}$  denotes the mediating variable under scrutiny, with ECI and ECS substituted separately. For instance, considering ECI,  $M_{pt}$  represents rural ECI in the  $p$ -th province during year  $t$ , while the remaining variables and model (2) adhere to the stated specifications. Initially, we regress Eq. (4), proceeding only if the coefficient  $\beta$  proves statistically significant. Should it fail to meet significance, the testing halts. Upon a substantial

$\beta_2$  in Eq. (5), we advance to Eq. (6); otherwise, the procedure ceases. Subsequently, if both coefficients  $\beta_3$  and  $\gamma$  in Eq. (6) demonstrate significant positivity, alongside a decrease in  $\beta_3$  relative to  $\beta$ , it signifies a partial mediation effect for ECI. Alternatively, if  $\beta_3$  lacks significance but  $\gamma$  remains significant, a full mediation effect for ECI is indicated.

### 4.3 Demonstration effect test

#### 4.3.1 Spatial correlation analysis

The Moran  $I$  index measures spatial autocorrelation, also known as spatial dependency, which quantifies the degree of correlation between the values of a specific attribute in a geographic area and the values of the same attribute in neighboring areas. Spatial autocorrelation tools assess spatial autocorrelation by considering both the location and value of features, calculating the Moran  $I$  index value,  $z$ -score, and  $p$ -value to determine the significance of the index. The Moran  $I$  index value ranges from  $-1$  to  $1$ , where values closer to  $-1$  indicate stronger negative spatial correlation, while values closer to  $1$  indicate more substantial spatial autocorrelation.

$$I = \frac{\sum_{i=1}^n \sum_{j \neq i}^n W_{ij} z_i z_j}{\sigma^2 \sum_{i=1}^n \sum_{j \neq i}^n W_{ij}} \tag{7}$$

Nevertheless, the Moran  $I$  index has limitations, as it typically relies on cross-sectional data, whereas our study employs panel data. Consequently, we substitute the spatial weight matrix used in the Moran  $I$  calculation and incorporate the time variable into the model to capture the dynamic changes in CEREC at the national level.

#### 4.3.2 Spillover effect analysis

As pilot provinces, Jiangsu and Anhui may exhibit policy spillover effects. Anhui's neighboring provinces include Shandong, Jiangsu, Zhejiang, Jiangxi, Hubei, and Henan, while Jiangsu's neighboring provinces include Shandong, Henan, Anhui, and Zhejiang. Consequently, CEREC in these provinces may also be affected

$$\ln Per\_C_{pt} = \alpha + \beta didn_{pt} + \delta x_{pt} + \tau_t + v_p + \epsilon_{pt} \tag{8}$$

where  $didn_{pt}$  represents the interaction term for spillover effects. defined as  $didn_{pt} = near_i \times time_t$ . Here,  $near_i$  distinguishes the treatment group from the control group: if province  $i$  is a neighboring province of pilot province,  $near_i$  is assigned a value of 1; otherwise, it is assigned a value of 0.  $post_t$  is a time dummy variable, set to 0 before selection and 1 in the selection year and after that. It's important to note that the control group refers to provinces initially designated as control group provinces, excluding neighboring provinces of the pilot area. A significantly positive estimated coefficient  $\beta$  for  $didn_{pt}$  suggests the presence of spatial spillover effects of the policy on neighboring provinces.

### 4.4 Extended analysis

The decoupling model assesses the dynamic relationship between two variables across different periods (Yang et al., 2021). By disrupting the correlation between urbanization

**Table 3** Tapio decoupling system

Status		$\Delta Per\_C/Per\_C^0$	$\Delta Urb/Urb^0$	$\varphi$
Decoupling	Enhancement	<0	>0	$\varphi < 0$
	Weakening	>0	>0	$0 < \varphi < 0.8$
	Decline	<0	<0	$\varphi > 1.2$
Negative decoupling	Enhancement	>0	<0	$\varphi < 0$
	Weakening	<0	<0	$0 < \varphi < 0.8$
	Growth	>0	>0	$\varphi > 1.2$
Coupling	Growth	>0	>0	$0.8 < \varphi < 1.2$
	Decline	<0	<0	$0.8 < \varphi < 1.2$

development and CEREC, resulting in divergent developmental trends within the same timeframe, it serves as a crucial indicator for evaluating the sustainable development of rural areas (Li et al., 2022). Hence, decoupling urbanization from carbon emissions is imperative to achieve peak carbon emissions in rural areas (Duan et al., 2022). In this study, the Tapio decoupling index is employed to examine the decoupling status of urbanization and CEREC across various provinces over the years.

$$\varphi^t = \frac{(Per\_C^t - Per\_C^0)/Per\_C^0}{(Urb^t - Urb^0)/Urb^0} = \frac{\Delta Per\_C/Per\_C^0}{\Delta Urb/Urb^0} \quad (9)$$

where  $\varphi^t$  represents the decoupling index,  $\Delta Per\_C$  and  $\Delta Urb$  represent the changes in CEREC and urbanization rate, respectively.  $Per\_C^t$  and  $Per\_C^0$  represent CEREC in year  $t$  and the baseline year, respectively, while  $Urb^t$  and  $Urb^0$  represent the urbanization rate in year  $t$  and the baseline year, respectively. The Tapio model defines eight decoupling states based on the magnitude of the  $\varphi$  value and the signs of  $\Delta Per\_C$  and  $\Delta Urb$ . The range of  $\varphi$  within 20% above and below 1 considered the coupling state, that is,  $\varphi \in (0.8, 1.2)$ , as shown in Table 3. The Tapio model considers elasticity in cases that fall near the critical point to avoid overinterpreting minor changes.

## 5 Empirical results and analysis

### 5.1 Impact of NCPINTU on CEREC

#### 5.1.1 Baseline regression results

The baseline regression results for Eq. (2) with CEREC as the dependent variable are shown in Table 4. The first column represents the model without control variables. Analysis of the regression results in the table reveals that NCPINTU positively influences CEREC. This effect remains significant even after gradually introducing control variables. The results in the fourth column indicate that when controlling for variables such as industrial structure, agricultural mechanization level, and rural per capita consumption level, the impact of NCPINTU on CEREC remains statistically significant at the 5% level. This suggests that, while considering the influence of other variables, the implementation of NCPINTU significantly promotes CEREC. Specifically, rural per capita carbon emissions have increased by 1.278 tons per year compared to non-pilot provinces. This

**Table 4** Results of baseline regression

<i>lnPer_C</i>	(1)	(2)	(3)	(4)
<i>Treat*period</i>	0.250** (0.127)	0.234** (0.104)	0.188* (0.099)	0.245** (0.117)
<i>I</i>		2.551*** (0.215)	3.156*** (0.237)	3.896*** (0.279)
<i>Mac</i>			0.061*** (0.010)	0.063*** (0.010)
<i>Csm</i>				-0.230*** (0.058)
<i>C</i>	-0.963*** (0.062)	-6.911*** (0.518)	-8.518*** (0.586)	-10.088*** (0.662)
<i>R</i> <sup>2</sup>	0.121	0.351	0.417	0.432

Values in brackets represent robust standard errors. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively

finding supports hypothesis 1, indicating that NCPINTU is associated with a narrowing urban-rural gap, improving rural household consumption levels, and increasing CEREC.

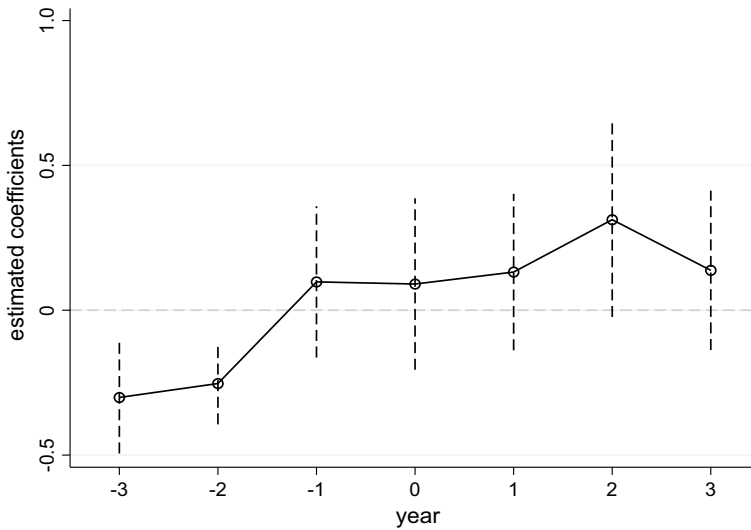
### 5.1.2 Parallel trends test

Previously, DID analysis revealed that NCPINTU promotes CEREC. However, a crucial prerequisite to substantiate this conclusion is that both the control group and treatment group demonstrate parallel trends before and after the implementation of the pilot policy. In line with established research frameworks, this study formulates the following regression model:

$$\ln Per\_C_{pt} = \alpha + \sum_{k=-3}^3 \beta_k did_{pt}^k + \delta x_{pt} + \tau_t + v_p + \varepsilon_{pt} \tag{10}$$

where  $did_{pt}^k$  represents the years of reform in the pilot provinces as the baseline. The variable "did" in Eq. (2) is split year by year into policy variables based on relative processing years. These variables are used to identify the policy effects of each year before and after the implementation of NCPINTU, denoted by  $\beta_k$ , thus capturing the differences in time trends between pilot and non-pilot provinces.  $\alpha$  is the intercept term, and other variables are consistent with the model setup in Eq. (2). This decomposition distinguishes the policy effects before and after NCPINTU in each treatment group province, using the policy variable obtained by splitting the variable  $did_{pt}$  in Eq. (2) according to the relative treatment year to identify the policy effects in each year before and after the implementation of the household registration system reform.  $\alpha$  is the intercept, and other variables are consistent with the model (2) specification.

As shown in Fig. 3, we assess whether CEREC satisfies the assumption of parallel trends before and after the implementation of NCPINTU. The horizontal axis denotes the relative time of policy implementation, while the vertical axis represents the estimated values of the parameter  $\beta_k$ . The circles on the graph represent the midpoints of the line segments, indicating the regression results of the relative time of policy implementation, and the length of the line segments represents the 95% confidence interval. The graph shows that the provinces implementing NCPINTU adhered to the null hypothesis of no significant



**Fig. 3** Parallel trend test

**Table 5** Robustness test

<i>lnPer_C</i>	(1)	(2)	(3)	(4)
<i>Treat*period</i>	0.250** (0.127)	0.246* (0.136)	0.223 (0.147)	0.296* (0.159)
<i>I</i>		2.278*** (0.218)	2.747*** (0.241)	3.838*** (0.302)
<i>Mac</i>			0.051*** (0.011)	0.054*** (0.011)
<i>Csm</i>				-0.319*** (0.066)
<i>C</i>	-0.963*** (0.062)	-6.346*** (0.527)	-7.619*** (0.598)	-9.913*** (0.709)
<i>R</i> <sup>2</sup>	0.121	0.313	0.357	0.388

Values in brackets represent robust standard errors. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively

difference between the treatment and control groups before and after the reform, suggesting that the data met the parallel trends assumption.

### 5.1.3 Robustness test

This study conducts robustness tests to improve the reliability and credibility of the earlier findings. Referring to relevant research, all control variables are lagged by one period to mitigate endogeneity issues arising from potential bidirectional causality. The regression results are shown in Table 5. In the first column, the estimated coefficient of NCPINTU is significantly positive at the 5% level. Similarly, the regression results in the second and



**Table 6** Analysis of fixed effects

	(1)	(2)
	<i>lnInt</i>	<i>lnCon</i>
<i>UPop</i>	-2.285*	4.185***
	(1.167)	(1.239)
<i>UEco</i>	-7.686***	2.478
	(1.773)	(2.292)
<i>USoc</i>	-0.475	-3.464**
	(0.890)	(1.361)
<i>UEnv</i>	-1.927***	8.855***
	(0.731)	(1.002)
<i>USpa</i>	5.194***	-2.905**
	(1.019)	(1.168)
<i>Csm</i>	-0.038	0.290***
	(0.056)	(0.086)
<i>Mac</i>	0.025***	-0.002
	(0.008)	(0.009)
<i>I</i>	2.280***	-1.417***
	(0.154)	(0.245)
<i>_cons</i>	-5.594***	1.960***
	(0.360)	(0.564)
<i>N</i>	300	300

Values in brackets represent robust standard errors. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively

fourth columns are statistically significant and demonstrate a consistent positive impact, aligning with the baseline regression results, thus confirming the robustness of the findings.

## 5.2 Effects mechanisms of NTU on CEREC

### 5.2.1 Fixed effects analysis

This study begins by exploring five dimensions: population, economy, society, ecology, and space. It then delves into the mechanisms through which NTU influences CEREC. The findings are presented in Table 6.

As shown in Table 6, the impact of NTU on ECI and ECS across five dimensions—population, economy, society, ecology, and space—is illustrated. Beginning with an examination of each dimension's effect on ECI, the first column reveals that population urbanization, economic urbanization, and ecological urbanization have a negative influence on ECI. However, the impact of social urbanization on ECI is not statistically significant, while spatial urbanization positively affects ECI. In the second column, population urbanization, economic urbanization, and ecological urbanization positively impact ECS, albeit with economic urbanization's effect being insignificant. Conversely, social urbanization and spatial urbanization negatively affect ECS.

Population urbanization primarily entails the migration of rural populations to urban areas, comprising mainly young and middle-aged adults. This phenomenon results in

a typical aging demographic in rural regions, leading to reduced consumption capacity among the elderly population and consequently a decline in ECI. Conversely, the urbanization of certain family members contributes to an overall increase in household income, leading to a higher utilization rate of household appliances, thus, an enhancement in ECS. As NTU progresses, the rural–urban disparity diminishes, and the economic status of rural households continues to improve. However, the transition to alternative energy consumption patterns lags behind income growth, primarily due to the high fixed costs associated with energy consumption, presenting a barrier to transition. Consequently, rural ECI experiences a decrease.

Social urbanization primarily entails the elevation of rural–urban income and consumption levels. As NTU progresses, the income disparity between urban and rural residents gradually diminishes, yet a notable gap in consumption levels persists. This discrepancy is particularly evident in rural ECS.

Ecological urbanization negatively impacts ECI but positively influences ECS, a phenomenon that is understandable. As a fundamental aspect of NTU development, ecological conservation gains traction, resulting in reduced ECI and enhanced ECS.

Spatial urbanization's development primarily signifies an increase in the per capita possession rate of social resources, where both urban and rural residents benefit from social development achievements. However, the rise in the per capita possession rate of social resources also implies heightened energy consumption to sustain resource operation and the potential wastage of idle resources. Consequently, this leads to an increase in ECI and a decline in ECS.

### 5.2.2 Mediation effects analysis

The baseline regression results indicate that NCPINTU significantly reduces CEREC. This study investigates further by selecting ECI and ECS as mediating variables to explore their influence pathways.

As shown in Table 7, the regression results for Eqs. (4), (5), and (6) analyze the mediating effects of ECI and ECS. Columns (1), (2), and (3) assess the mediating effect on ECI. In the first column, the regression outcomes indicate that the implementation of NCPINTU significantly promotes CEREC at a 5% significance level. The second column, with ECI as the dependent variable, illustrates that NCPINTU significantly increases ECI at a 5% significance level. In the third column, when ECI is included as a control variable in the regression model, the coefficient representing the impact of NCPINTU on CEREC is  $-0.119$ , significant at a 10% level. Compared to the regression results in the first column, where ECI is not included as a control variable, the coefficient of the explanatory variable decreases. Additionally, the coefficient for ECI is  $0.172$  and significant at a 5% level. This suggests that ECI plays a partial mediating role in the impact pathway of NCPINTU on CEREC. Hypothesis 2 is confirmed.

Columns (1), (4), and (5) analyze the mediating effects on ECS. In the fourth column, ECSECS is regressed, revealing that the coefficient for NCPINTU is  $-0.123$  and significant at a 10% level. However, in the fifth column, when ECS is included as a control variable, the coefficient becomes  $0.105$  and is insignificant. This suggests that NCPINTU promotes CEREC by inhibiting ECS. The insignificance of the coefficient for the explanatory variable in the fifth column implies that ECS plays a complete mediating role. Therefore, Hypothesis 3 is rejected.

**Table 7** Test of mediating effect

	(1) <i>lnPer_C</i>	(2) <i>lnInt</i>	(3) <i>lnPer_C</i>	(4) <i>lnCon</i>	(5) <i>lnPer_C</i>
<i>Treat*period</i>	0.245** (0.117)	0.172** (0.669)	-0.119* (0.023)	-0.123* (0.716)	0.105 (0.103)
<i>lnInt</i>			2.113*** (0.041)		
<i>lnCon</i>					-1.139*** (0.109)
<i>Csm</i>	-0.230*** (0.058)	-0.293*** (0.031)	0.389*** (0.031)	0.338*** (0.044)	0.154* (0.086)
<i>Mac</i>	0.063*** (0.010)	0.026*** (0.004)	0.009** (0.004)	-0.011** (0.005)	0.051*** (0.006)
<i>I</i>	3.896*** (0.279)	1.537*** (0.128)	0.649*** (0.132)	-1.671*** (0.227)	1.993*** (0.308)
<i>C</i>	-10.088*** (0.662)	-4.099*** (0.297)	-1.428*** (0.312)	2.925*** (0.519)	-6.757*** (0.666)
<i>R</i> <sup>2</sup>	0.432	0.353	0.948	0.271	0.706

Values in brackets represent robust standard errors. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively

### 5.2.3 Variance decomposition

By conducting variance decomposition of the prediction errors, we can assess the contribution of orthogonalized shocks of all variables to the mean square error of one specific variable, thus examining the degree of mutual influence among the variables.

As shown in Table 8, the lagged one-period impacts of population urbanization, economic urbanization, social urbanization, ecological urbanization, and spatial urbanization are considered as shock variables to explore their effects on CEREC, ECI, and ECS. Initially, analyzing the impacts of each shock variable on carbon emissions, economic urbanization shows the largest contribution rate, accounting for over 67.71%, followed by social urbanization and ecological urbanization with contribution rates stabilizing at 2.43% and 1.10% respectively. Population urbanization and spatial urbanization have relatively smaller contribution rates to carbon emissions, stabilizing at 0.63% and 0.47% respectively. Moving to the impacts of shock variables on ECI, economic urbanization exhibits the highest contribution rate, exceeding 86.22%, followed by ecological urbanization and spatial urbanization with contribution rates of 1.40% and 1.02% respectively. Population urbanization and social urbanization have contribution rates of 0.23% and 0.54% respectively. Lastly, considering the impacts of shock variables on ECS, economic urbanization still maintains the highest contribution rate, exceeding 80.75%, followed by social urbanization, spatial urbanization, and ecological urbanization with contribution rates of 3.71%, 2.95%, and 1.03% respectively. Population urbanization has the smallest contribution rate at 0.8%.

**Table 8** The variance decomposition results of NTU on CEREC, ECI, and ECS

Variable	Period	Shock variables				
		dUPop	dUEco	dUSoc	dUEnv	dUSpa
<i>dlnPer_C</i>	1	0.003	0.090	0.002	0.006	0.005
	2	0.006	0.199	0.020	0.011	0.005
	3	0.006	0.296	0.024	0.011	0.005
	4	0.006	0.379	0.024	0.011	0.005
	5	0.006	0.449	0.024	0.011	0.005
	6	0.006	0.508	0.024	0.011	0.005
	7	0.006	0.560	0.024	0.011	0.005
	8	0.006	0.604	0.024	0.011	0.005
	9	0.006	0.643	0.024	0.011	0.005
	10	0.006	0.677	0.024	0.011	0.005
<i>dlnInt</i>	1	0.002	0.001	0.004	0.002	0.008
	2	0.002	0.076	0.005	0.014	0.010
	3	0.002	0.181	0.005	0.014	0.010
	4	0.002	0.300	0.005	0.014	0.010
	5	0.002	0.423	0.005	0.014	0.010
	6	0.002	0.542	0.005	0.014	0.010
	7	0.002	0.648	0.005	0.014	0.010
	8	0.002	0.737	0.005	0.014	0.010
	9	0.002	0.808	0.005	0.014	0.010
	10	0.002	0.862	0.005	0.014	0.010
<i>dlnCon</i>	1	0.007	0.294	0.000	0.008	0.020
	2	0.008	0.503	0.030	0.010	0.029
	3	0.008	0.612	0.036	0.010	0.030
	4	0.008	0.676	0.037	0.010	0.030
	5	0.008	0.717	0.037	0.010	0.030
	6	0.008	0.747	0.037	0.010	0.030
	7	0.008	0.768	0.037	0.010	0.030
	8	0.008	0.784	0.037	0.010	0.030
	9	0.008	0.797	0.037	0.010	0.030
	10	0.008	0.808	0.037	0.010	0.030

### 5.3 Demonstration effect test of NCPINTU

#### 5.3.1 Spatial correlation analysis

Spatial autocorrelation analysis was conducted on CEREC from 2010 to 2019 (Jiang et al., 2022). The results are presented in Table 9. From 2010 to 2012, the overall results were not significant. However, starting in 2013, CEREC began to exhibit a positive spatial autocorrelation trend, coinciding with the implementation period of NCPINTU. This suggests that an optimized energy consumption pattern has a positive spillover effect.

**Table 9** Moran's I of CEREC, 2010–2019

Year	Moran's I	Year	Moran's I
2010	0.067 (0.004)	2015	0.111* (0.006)
2011	0.040 (0.004)	2016	0.182*** (0.006)
2012	0.050 (0.005)	2017	-0.013 (0.001)
2013	0.102* (0.005)	2018	0.116** (0.005)
2014	0.103* (0.005)	2019	-0.075* (0.000)

Values in brackets represent robust standard errors. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively

**Table 10** Test of spillover effect

<i>InPer_C</i>	(1)	(2)	(3)	(4)
<i>Treat*period</i>	0.214 (0.149)	0.159 (0.128)	0.184* (0.109)	0.198* (0.108)
<i>I</i>		2.554*** (0.212)	3.390*** (0.219)	4.015*** (0.299)
<i>Mac</i>			0.079*** (0.010)	0.077*** (0.009)
<i>Csm</i>				-0.218*** (0.075)
<i>C</i>	-0.937*** (0.074)	-6.888*** (0.514)	-9.038*** (0.544)	-10.347*** (0.697)
<i>R</i> <sup>2</sup>	0.059	0.305	0.402	0.411

Values in brackets represent robust standard errors. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively

### 5.3.2 Spillover effect analysis

The analysis of policy spillover effects is presented in Table 10. By excluding the provinces involved in NCPINTU and considering their neighboring provinces as the experimental group, while the remaining provinces serve as the control group, the study examines the impact of NCPINTU on the neighboring provinces of the pilot provinces to explore the demonstration effect of the policy.

From the regression results in columns (3) and (4), it can be observed that, after excluding the influence of other control variables, the spillover effect of NCPINTU is significantly positive, resulting in an average increase of 1.219 tons per person per year. In rural areas, production and lifestyle are characterized by a relatively open nature, and there exists a heightened level of interaction among neighbors. This heightened interaction renders rural households susceptible to the influences of other neighboring rural households. Additionally, communication channels between neighboring villages are established, resulting in the formation of an extensive social network. Taking Jiangsu province as an example, as one of the first provinces selected for NCPINTU, its CEREC has been effectively mitigated. The implementation of NCPINTU often has a significant demonstration effect,

**Table 11** Tapio decoupling statistics of urbanization and CEREC in Chinese provinces, 2011–2019

Status		Number of Samples in Each Time Period		
		2011–2013	2014–2019	2010–2019
Decoupling	Enhancement	15	29	44
	Weakening	6	22	28
Negative decoupling	Decline	0	5	5
	Enhancement	0	0	0
	Weakening	0	0	0
Coupling	Decline	65	117	182
	Growth	4	7	11
	Decline	0	0	0

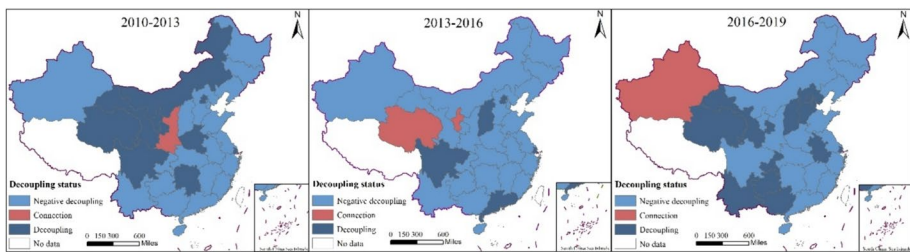
which aligns with the original intention of the policy. Jiangsu's neighboring provinces include Shandong, Anhui, Zhejiang, and Shanghai, with Anhui being a pilot province and excluded from the analysis. The rural household lifestyle in Jiangsu province significantly affects the neighboring provinces. The study excludes the provinces involved in NCPINTU and designates their neighboring provinces as the experimental group, while the remaining provinces constitute the control group. This approach is aimed at examining the impact of NCPINTU on the neighboring provinces of the pilot provinces, thus exploring the policy's demonstration effect (Balado-Naves et al., 2023).

## 5.4 Expanded analysis

Using 2010 as the base year, this study calculated the decoupling elasticity coefficients of urbanization and CEREC for 30 provinces in China during 2011–2019 using the Tapio model (Yu X. et al., 2020). As depicted in Table 11, the sample was divided into two periods based on the pilot year. Between 2011 and 2013, out of 90 samples, approximately 72.22% indicated negative decoupling growth, while 16.67% of the provinces experienced decoupling strengthening, and 4.44% showed connected growth between carbon emissions and urbanization. From 2014 to 2019, with a total of 180 samples, 65% indicated negative decoupling growth, 16.11% experienced decoupling strengthening, and 3.89% showed connected growth. By comparing the two periods, it was observed that the proportion of samples in negative decoupling growth decreased by 7.22%, while those in decoupling to a lesser degree increased by 5.56%. The proportion of samples in the decoupling strengthening state remained relatively stable. This indicates a transition of some samples from negative decoupling growth to decoupling to a lesser degree. In essence, while CEREC and urbanization rates continue to rise, the decoupling index declines to some extent. This implies that the implementation of NCPINTU will partially attenuate the rate of CEREC growth with the urbanization rate's increase. Furthermore, comparing the proportion of samples in the connected growth state between the two periods, there was a decrease of 0.56%. This indicates reduced dependency on energy consumption in the urbanization development process. It suggests that while promoting urbanization further, embracing low-carbon and environmentally friendly consumption patterns will aid in reaching the peak of carbon emissions (Du H. B. et al., 2021).

**Table 12** Decoupling index of urbanization rate and CEREC

Province	2010–2013	2013–2016	2016–2019	Province	2010–2013	2013–2016	2016–2019
Beijing	-27.628	-32.973	-33.783	Henan	0.460	32.688	2.730
Tianjin	6.261	17.827	-8.909	Hubei	3.776	5.300	4.899
Hebei	9.508	2.022	-0.684	Hunan	-1.312	1.618	2.574
Shanxi	1.819	0.470	-5.334	Guangdong	7.256	-15.264	58.372
Inner Mon- golia	-5.438	3.625	6.141	Guangxi	3.401	4.588	-0.723
Liaoning	4.880	6.986	39.626	Hainan	12.705	6.408	2.703
Jilin	35.035	3.081	76.169	Chongqing	3.438	7.798	-7.752
Heilongjiang	11.466	2.490	2.687	Sichuan	-1.400	0.104	3.592
Shanghai	-7.953	19.101	-87.164	Guizhou	1.258	1.569	-1.287
Jiangsu	7.826	3.102	6.164	Yunnan	2.477	2.630	0.389
Zhejiang	4.637	3.917	1.342	Shaanxi	1.075	1.618	1.824
Anhui	9.815	3.854	-2.183	Gansu	-1.316	2.393	0.138
Fujian	2.930	2.322	4.184	Qinghai	0.428	0.953	-2.012
Jiangxi	1.535	5.186	5.236	Ningxia	-2.427	1.105	1.396
Shandong	4.957	2.910	8.959	Xinjiang	3.376	13.877	1.009



**Fig. 4** Spatial pattern of decoupling status in various provinces of China based on Tapio decoupling index, 2010–2019. This figure is based on the standard map with the approval number GS(2023) 2767 downloaded from the National Administration of Surveying, Mapping, and Geoinformation’s Standard Map Service website. The basemap has not been modified

The decoupling index between the urbanization rate and carbon emissions level for each province in China was calculated for three time periods: 2010–2013, 2013–2016, and 2016–2019, based on the Tapio decoupling model. The results are shown in Table 12.

As shown in Fig. 4, visual analysis was conducted on the decoupling status between urbanization development level and CEREC for different stages across provinces.

From 2010 to 2013, Shaanxi Province exhibited a poor decoupling status. However, between 2013 and 2016, Shaanxi Province recovered its decoupling status, while Qinghai Province and Ningxia Province shifted to a connecting status. Overall, provinces with poor decoupling status were mainly concentrated in the western region.

From 2016 to 2019, all provinces in China, except for Xinjiang, attained a decoupling status. Furthermore, some provinces transitioned from a negative decoupling status to a decoupling status, indicating a gradual decrease in the growth rate of CEREC while maintaining a steady increase in the level of urbanization.

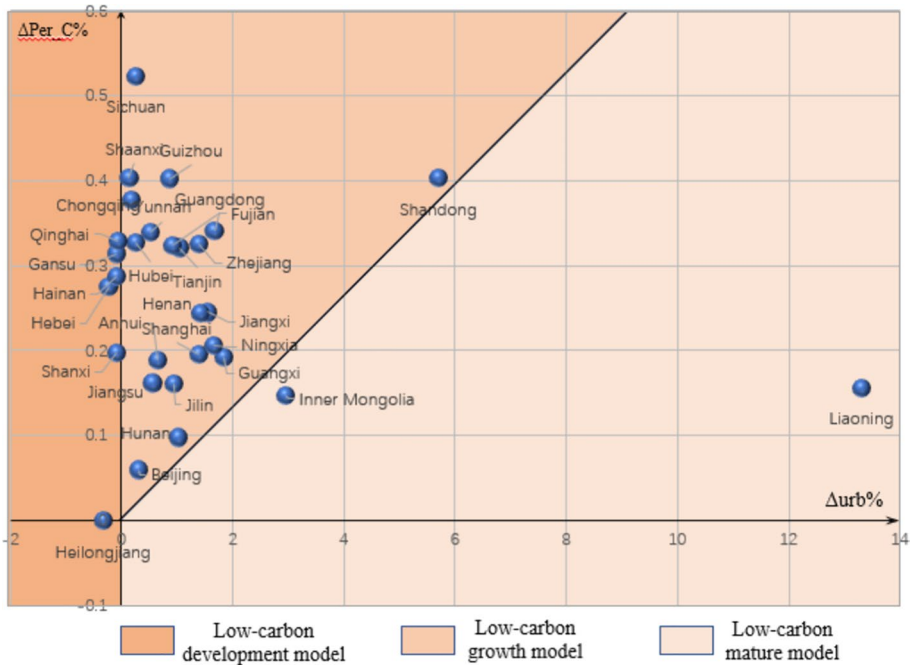


Fig. 5 Quadrants of development types of each province, 2010–2019

According to the study conducted by Yu et al. (2020), the threshold value of relative growth rates between urbanization and CEREC, denoted as  $\varphi$ , was established as 1. This threshold value delineates the classification of provinces into different low-carbon development types. When  $\varphi = 1$ , the growth rate of urbanization equals the growth rate of CEREC. When  $\varphi < 1$ , urbanization grows faster than CEREC, and conversely, when  $\varphi > 1$ . Incorporating this adjusted threshold value into the Tapio decoupling model framework allowed for the determination of decoupling types for each province during the period 2010–2019, considering their elasticity coefficients and urbanization growth rates. Provinces were categorized into three types: the low-carbon mature type ( $\Delta\text{Urb} > 0$  and  $\varphi < 1$ ), indicating that CEREC growth is slower than urbanization or even decreasing while urbanization continues to grow, representing the desired scenario of coordinated development; the low-carbon growing type ( $\Delta\text{Urb} > 0$  and  $\varphi \geq 1$ ), indicating that CEREC growth outpaces urbanization, requiring further reductions in emissions despite ongoing urbanization; and the low-carbon catching-up type ( $\Delta\text{Urb} < 0$ ), representing provinces with negative urbanization growth requiring prompt adjustments.

As shown in Fig. 5, based on the mentioned earlier classification of low-carbon development types, most provinces fall into the low-carbon growing type, where CEREC growth exceeds urbanization growth. However, Liaoning and Inner Mongolia provinces have achieved the optimal scenario of positive urbanization growth alongside a decrease in CEREC.



## 6 Conclusions and recommendations

This paper employs a panel dataset covering 30 provinces in China from 2010 to 2019 and employs DID to analyze the impact of NCPINTU on CEREC to elucidate its underlying mechanisms. The findings indicate: Firstly, NCPINTU significantly promotes CEREC, a conclusion robust to a battery of sensitivity tests, corroborating previous assertions regarding urbanization's carbon emissions-driving effect (Zhang et al., 2016). Secondly, NCPINTU enhances CEREC by both increasing ECI and inhibiting the optimization of ECS, with ECI and ECS acting as mediators. Thirdly, the policy spillover effect of the pilot areas significantly promotes CEREC, as evidenced by a noticeable increase in carbon emissions in neighboring provinces following the implementation of pilot policies. Compared to previous studies, this paper introduces spatial effects (Yang, 2023). China's rural areas exhibit typical characteristics of a close-knit community, with significant neighborly effects, leading to stronger exemplarity in their behavioral decisions. This aligns more closely with the reality of rural consumption scenarios, thereby making the conclusions of this paper more persuasive. Fourthly, NCPINTU influences ECI and ECS through five dimensions: population urbanization, economic urbanization, social urbanization, ecological urbanization, and spatial urbanization, thereby promoting CEREC. It enriches the study of the mechanisms underlying the impact of urbanization on CEREC. This multidimensional approach not only provides a more comprehensive perspective on understanding the impact of urbanization on rural household carbon emissions, but also offers more accurate and targeted guidance for future policy formulation.

As carbon peaking and carbon neutrality policies continue to gain traction globally, carbon emissions have emerged as a pivotal concern. The significance of addressing CEREC cannot be overstated. Understanding its dynamics and mechanisms within the NTU process is imperative for shaping a new era of low-carbon and eco-friendly rural development in China. Moreover, the insights garnered from this study offer valuable lessons for other nations seeking to foster synergies between urbanization and CEREC. Based on the above conclusion, this study presents the following suggestions: Firstly, with the implementation of NCPINTU, urbanization priorities should shift from mere infrastructure development to fostering integrated and sustainable urban–rural growth. We need to focus on the green and sustainable development concept. Accelerate the process of green urbanization and promote low-carbon urban development. Through the establishment of exhibition boards, distribution of publicity manuals, and other means, we can promote green, low-carbon, energy-saving practices to the public and enterprises. Advise people to travel green and adopt a low-carbon lifestyle. Secondly, given that rural areas are increasingly contributing to carbon emissions, adopting a low-carbon consumption paradigm is imperative. Measures such as incentivizing clean energy usage, particularly by substituting coal with electricity through policy interventions and subsidies, can significantly mitigate ECI, enhance ECS, and alleviate CEREC challenges. Thirdly, in pilot areas, the government can increase financial subsidies and policy support to promote the innovative application and demonstration of rural renewable energy. While non-pilot regions require focused support in infrastructure, education, and incentivization, they also need. Harnessing the demonstrative impact of pilot areas and scaling up low-carbon consumption models nationwide will be instrumental in advancing global carbon peaking efforts. Leveraging the demonstrative effect within pilot regions to extend initiatives from individual points to broader areas, establishing a nationwide model of low-carbon consumption. Lastly, prioritizing coupled development between NCPINTU and carbon emission targets should involve meticulous

planning and construction focusing on population, economic, social, ecological, and spatial urbanization. This concerted effort will ensure China's carbon emission objectives align harmoniously with NTU construction, fostering a concurrent transition towards low-carbon development. This endeavor aims to contribute to and serve as an exemplar for global endeavors toward carbon peak achievement.

Despite these significant findings and implications, this study still presents certain shortcomings and derivative aspects that can be further explored in future research. Firstly, the short temporal span of the data, covering only 11 years from 2010 to 2020, may overlook longer-term dynamic factors that evolve over time. To address this, future research should extend the time horizon and incorporate potential economic and social environmental factors into the analysis. Secondly, the study's focus on Chinese samples alone limits the generalizability of the conclusions. To enhance the international relevance of the findings, future research should incorporate samples from multiple countries and strive for more comprehensive datasets to further strengthen the reliability of the conclusions. Lastly, as a macro-level analysis, it is unable to explore the micro-level impacts of NTU on NTUNTU. Future studies could focus on the specific micro-level impacts of NTU on NTUNTU to verify and improve the shortcomings of existing research. By addressing these limitations, we can enhance the comprehensiveness, generalizability, and reliability of our research in this field.

**Acknowledgements** This study is supported by Soft Science Research Project of Shaanxi Province (No: 2022KRM032; 2023-CXRKX-103), Social Science Foundation of Shaanxi Province (No: 2021D058; 2022D022), Philosophy and Social Science Research Project of Shaanxi Province (No: 2024QN022), Humanities and Social Sciences Base Project of the Fundamental Research Funds for the Central Universities (No: 2452024333).

**Data availability** The data that support the findings of this study are openly available in China Energy Statistical Yearbook, National Bureau of Statistics at [http://www.stats.gov.cn/tjsj/tjcbw/201303/t20130318\\_451533.html](http://www.stats.gov.cn/tjsj/tjcbw/201303/t20130318_451533.html).

## Declarations

**Conflict of interest** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## References

- Balado-Naves, R., Banos-Pino, J. F., & Mayor, M. (2023). Spatial spillovers and world energy intensity convergence. *Energy Economics*, 124, 106807. <https://doi.org/10.1016/j.eneco.2023.106807>
- Bhattacharyya, S. C. (2015). Influence of India's transformation on residential energy demand. *Applied Energy*, 143, 228–237. <https://doi.org/10.1016/j.apenergy.2015.01.048>
- Cao, X., Gao, Y., & Liu, Z. (2021). Analysis of the impact of rural population urbanization on residents' carbon emission of living energy consumption. *Chinese Rural Economy*, 10, 64–83.
- Chen, M., Gong, Y., Lu, D., & Ye, C. (2019). Build a people-oriented urbanization: China's new-type urbanization dream and Anhui model. *Land Use Policy*, 80, 1–9. <https://doi.org/10.1016/j.landusepol.2018.09.031>
- Chen, M., Liu, W., Lu, D., Chen, H., & Ye, C. (2018). Progress of China's new-type urbanization construction since 2014: A preliminary assessment. *Cities*, 78, 180–193. <https://doi.org/10.1016/j.cities.2018.02.012>
- Cheng, T., & Da, Y. (2022). Income Equality, Carbon Emissions, and Economic Growth. *Soft Science*, 36(3), 68–74. <https://doi.org/10.13956/j.ss.1001-8409.2022.03.10>
- Cheng, N., Sang, Y., & Li, B. (2023). Research on the development of “carbon unleashing” under the “dual carbon” goal in China. *Reform*, 12, 151–162.

- Clausen, L. T., & Rudolph, D. (2020). Renewable energy for sustainable rural development: Synergies and mismatches. *Energy Policy*, 138, 111289. <https://doi.org/10.1016/j.enpol.2020.111289>
- Deng, B., & Zhong, F. (2023). Leading or constraining? development of new-type urbanization under economic growth targets. *Land*, 12(4), 916. <https://doi.org/10.3390/land12040916>
- Du, H., Wei, W., Zhang, X., & Ji, X. (2021a). Spatial-temporal pattern evolution and influencing factors of carbon emission from the yellow river basin: Based on DMSP/OLS and NPP/VIIRS nighttime light data. *Geographical Research*, 40(7), 2051–2065.
- Du, K., Shao, S., & Yan, Z. (2021b). Urban residential energy demand and rebound effect in China: A stochastic energy demand frontier approach. *Energy J.*, 42, 175–193. <https://doi.org/10.5547/01956574.42.4.kdu>
- Duan, X., Li, X., Tan, W., & Xiao, R. (2022). Decoupling relationship analysis between urbanization and carbon emissions in 33 African countries. *Heliyon*, 8(9), e10423. <https://doi.org/10.1016/j.heliyon.2022.e10423>
- Fang, C. (2019). The Regularity and Key Directions of High-Quality Development of New Urbanization in China. *Geographical Research*, 13–22.
- Gao, X., & Han, X. (2022). Spatial differentiation and influencing factors of carbon emissions in the yellow river basin. *Economic Geography*, 39(1), 13–23. <https://doi.org/10.15931/j.cnki.1006-1096.2022.01.003>
- Han, H., & Wu, S. (2018). Rural residential energy transition and energy consumption intensity in China. *Energy Econ.*, 74, 523–534. <https://doi.org/10.1016/j.eneco.2018.04.033>
- Huang, R., Wang, Z., Ding, G., Gong, Y., & Liu, C. (2016). Analysis and trend prediction of carbon emission factors of energy consumption in Jiangsu province based on the STIRPAT model. *Geographical Research*, 35(4), 781–789.
- Ji, Z., Lai, X., & Jia, L. (2016). Measurement and driving factors of household sector carbon emission from energy consumption: A study on China. *Chinese Population, Resources and Environment*, 26(5), 64–72.
- Jiang, J., Zhu, S., Wang, W., Li, Y., & Li, N. (2022). Coupling coordination between new urbanisation and carbon emissions in China. *Science of the Total Environment*, 850, 158076. <https://doi.org/10.1016/j.scitotenv.2022.158076>
- Li, Y., & Zhang, H. (2016). Regional differences in the impact of urbanization on household CO<sub>2</sub> emissions—an analysis based on provincial panel data in China. *Resources Science*, 38(3), 545–556. <https://doi.org/10.18402/resci.2016.03.17>
- Li, L., Gao, X., & Huang, J. (2020). Prospects for major issues in China's new urbanization development during the "14th five-year plan" period. *management world*, 36(11), 7–22. <https://doi.org/10.19744/j.cnki.11-1235/f.2020.0165>
- Li, Y., Gao, K., & Jiang, H. (2022). Carbon balance pressure and decoupling relationship between new urbanization and carbon emissions in the core area of Yangtze river delta urban agglomeration. *Economic Geography*, 42(12), 72–81. <https://doi.org/10.15957/j.cnki.jjdl.2022.12.008>
- Li, Y., & Gao, K. (2022). The impact of green urbanization on carbon emissions: The case of new urbanization in China. *Frontiers in Environmental Science*, 10, 1070652. <https://doi.org/10.3389/fenvs.2022.1070652>
- Lin, B., & Zhu, J. (2021). Impact of China's new-type urbanization on energy intensity: A city-level analysis. *Energy Economics*, 99, 105292. <https://doi.org/10.1016/j.eneco.2021.105292>
- Liu, Y., Yan, B., & Wang, Y. (2016). Major issues and transformation countermeasures of urban-rural development in China in the new period. *Economic Geography*, 36(7), 1–8. <https://doi.org/10.15957/j.cnki.jjdl.2016.07.001>
- Liu, J., Li, X., & Zhong, S. (2022a). Does innovation efficiency promote energy consumption intensity? *New Evidence from China. Energy Rep.*, 8, 426–436. <https://doi.org/10.1016/j.egyr.2022.05.096>
- Liu, J., Murshed, M., Chen, F., Shahbaz, M., Kirikkaleli, D., & Khan, Z. (2021). An empirical analysis of the household consumption-induced carbon emissions in China. *Sustain. Prod. Consump.*, 26, 943–957. <https://doi.org/10.1016/j.spc.2021.01.006>
- Liu, M., Yang, X., Wen, J., Wang, H., Feng, Y., Lu, J., Chen, H., Wu, J., & Wang, J. (2023). Drivers of China's carbon dioxide emissions: Based on the combination model of structural decomposition analysis and input-output subsystem method. *Environmental Impact Assessment Review*, 100, 107043. <https://doi.org/10.1016/j.eiar.2023.107043>
- Liu, Y., Jiang, Y., Liu, H., Li, B., & Yuan, J. (2022b). Driving factors of carbon emissions in China's municipalities: A LMDI approach. *Environmental Science and Pollution Research*, 29, 21789–21802. <https://doi.org/10.1007/s11356-021-17277-w>
- Lu, Y., & Chen X. (2023). Digital economy, new-type urbanization, and carbon emissions: Evidence from China. *Environmental Progress & Sustainable Energy*, 14045. <https://doi.org/10.1002/ep.14045>

- Meng, W., Yuan, G., & Sun, Y. (2023). Expansion of social networks and household carbon emissions: Evidence from household survey in China. *Energy Policy*, 174, 113460. <https://doi.org/10.1016/j.enpol.2023.113460>
- Qiu, H., Yan, J., Li, D., & Han, W. (2015). Analysis of the current situation, development trend, and determinants of rural household energy consumption in China: An empirical study based on two periods and four provinces. *China Soft Science*, 11, 28–38.
- Qu, J., Liu, L., Zeng, J., Zhang, Z., Wang, L., & Wang, Q. (2014). Analysis of driving factors of carbon emissions from urban and rural residents' living in China. *Chinese Population, Resources and Environment*, 24(8), 33–41.
- Shao, S., Zhang, K., & Dou, J. (2019). Energy saving and emission reduction effects of economic agglomeration: Theory and Chinese experience. *Management World*, 35(1), 36–60+226. <https://doi.org/10.19744/j.cnki.11-1235/f.2019.0005>
- Shen, H., Tao, S., Chen, Y., Ciais, P., Güneralp, B., Ru, M., Zhong, Q., Yun, X., Zhu, X., Huang, T., Tao, W., Chen, Y., Li, B., Wang, X., Liu, W., Liu, J., & Zhao, S. (2017). Urbanization-induced population migration has reduced ambient PM 2.5 concentrations in China. *Science Advances*, 3(7), e1700300. <https://doi.org/10.1126/sciadv.1700300>
- Sun, H., & Sun, F. (2016). Empirical Evidence on the impact of urban-rural income gap on carbon emissions: On the promotion of "Efficiency" by "Fairness". *Macroeconomic Research*, 1, 47–58. <https://doi.org/10.16304/j.cnki.11-3952/f.2016.01.005>
- Wang, L., Wang, H., & Dong, Z. (2020). Policy bias effects test under the conditions of economic growth and environmental quality compatibility: a perspective of environmental technological progress direction. *Management World*, 36(3), 39–60. <https://doi.org/10.19744/j.cnki.11-1235/f.2020.0033>
- Wang, R., Zhang, H., Qiang, W., Li, F., Peng, J. (2021). Spatial characteristics and influencing factors of carbon emissions in county-level cities of China based on urbanization. *Progress in Geography*, 40(12), 1999–2010. <https://doi.org/10.18306/dlkxjz.2021.12.002>
- Wang, Y., Li, L., Kubota, J., Han, R., Zhu, X., & Lu, G. (2016). Does urbanization lead to more carbon emission? Evidence from a panel of BRICS countries. *Applied Energy*, 168, 375–380. <https://doi.org/10.1016/j.apenergy.2016.01.105>
- Yan, C., Li, T., & Lan, W. (2016). Financial development, innovation and carbon emissions. *Financial Research*, 1, 14–30.
- Yang, L., & Sun, Z. (2015). Evaluation of the development level of new western urbanization based on entropy method. *Economic Issues*, 3, 115–119. <https://doi.org/10.16011/j.cnki.jjw.2015.03.023>
- Yang, F. (2023). Impact of agricultural modernization on agricultural carbon emissions in China: A study based on the spatial spillover effect. *Environmental Science and Pollution Research*. <https://doi.org/10.1007/s11356-023-28350-x>
- Yang, J., Hao, Y., & Feng, C. (2021). A race between economic growth and carbon emissions: What play important roles towards global low-carbon development? *Energy Econ.*, 100, 105327. <https://doi.org/10.1016/j.eneco.2021.105327>
- Yang, S., Liu, S., Wu, T., & Zhai, Z. (2022). Does new-type urbanization curb haze pollution? A case study from China. *Environmental Science and Pollution Research*, 30(8), 20089–20104. <https://doi.org/10.1007/s11356-022-23379-w>
- Yang, L., Liang, Z., Yao, W., Zhu, H., Zeng, L., & Zhao, Z. (2023). What are the impacts of urbanisation on carbon emissions efficiency? Evidence from Western China. *Land*, 12(9), 1707. <https://doi.org/10.3390/land12091707>
- Yu, B. (2021). Ecological effects of new-type urbanization in China. *Renewable and Sustainable Energy Reviews*, 135, 110239. <https://doi.org/10.1016/j.rser.2020.110239>
- Yu, J., Yu, Y., & Jiang, T. (2022). Structural factors influencing energy carbon emissions in China's service industry: An input-output perspective. *Environmental Science and Pollution Research*, 29, 49361–49372. <https://doi.org/10.1007/s11356-022-19287-8>
- Yu, X., Chen, N., & Li, M. (2020). Characteristics of carbon emissions and carbon reduction paths in China's low-carbon pilot cities. *Chinese Population, Resources and Environment*, 30(7), 1–9.
- Yu, X., Li, Y., Chen, H., & Li, C. (2019). Influence of environmental regulation and energy endowment on regional carbon emissions from the perspective of "resource curse." *Chinese Population, Resources and Environment*, 29(5), 52–60.
- Zhang, M., Huang, X., & Chuai, X. (2019). Calculation and influencing factors of carbon emissions in Chinese Cities. *Ecological Economy*, 35(9), 13–19+74.
- Zhang, J., Yang, J., & Sheng, P. (2016). Impact of urbanization on carbon emissions in China and Its channels of action. *Chinese Population, Resources and Environment*, 26(2), 47–57.

- Zhang, Y., Wang, F., & Zhang, B. (2023). The impacts of household structure transitions on household carbon emissions in China. *Ecological Economics*, 206, 107734. <https://doi.org/10.1016/j.ecolecon.2022.107734>
- Zhao, B., Wang, K.-L., & Xu, R.-Y. (2023). Fiscal decentralization, industrial structure upgrading, and carbon emissions: Evidence from China. *Environmental Science and Pollution Research*, 30, 39210–39222. <https://doi.org/10.1007/s11356-022-24971-w>
- Zheng D. C., Liu W. X., Li X. X., Lin Z. Y., & Jiang H. (2018). Research on carbon emission diversity from the perspective of urbanization. *Applied Ecology and Environmental Research*, 16(5), 6643–6654. [https://doi.org/10.15666/aeer/1605\\_66436654](https://doi.org/10.15666/aeer/1605_66436654)

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.

## Authors and Affiliations

**Man Wang<sup>1</sup> · Manman Gao<sup>1</sup> · Huimin Cao<sup>1</sup> · Zhenyu Yan<sup>1</sup> · Muhammad Taimoor<sup>1</sup> · Jiapeng Xu<sup>1</sup>**

✉ Jiapeng Xu  
xujp@nwsuaf.edu.cn

Man Wang  
wangman@nwafu.edu.cn

Manman Gao  
gaomanman@nwafu.edu.cn

Huimin Cao  
caohm@nwafu.edu.cn

Zhenyu Yan  
yanzhenyu@nwsuaf.edu.cn

Muhammad Taimoor  
taimooruaf@gmail.com

<sup>1</sup> College of Economics and Management, Northwest A&F University, No. 3 Taicheng Road, Yangling 712100, Shaanxi, People's Republic of China